AUTOMATED DIAGNOSIS OF BRAIN TUMOR IN MRI IMAGES USING DEEP LEARNING TECHNIQUES

MASTER OF TECHNOLOGY

COMPUTER SCIENCE AND ENGINEERING

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TOPIC APPROVAL PERFORMA

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PROPOSED TOPIC : Automated Diagnosis of Brain tumor in MRI images using Deep Learning techniques

Qualitative Assessment of Proposed Topic by PAC		
Sr.No.	**Parameter**	**Rating (out of 10)**
1	Project Novelty: Potential of the project to create new knowledge	8.30
2	Project Feasibility: Project can be timely carried out in-house with low-cost and available resources in the University by the students.	8.30
3	Project Academic Inputs: Project topic is relevant and makes extensive use of academic inputs in UG program and serves as a culminating effort for core study area of the degree program.	8.30
4	Project Supervision: Project supervisor’s is technically competent to guide students, resolve any issues, and impart necessary skills.	8.70
5	Social Applicability: Project work intends to solve a practical problem.	7.90
6	Future Scope: Project has potential to become basis of future research work, publication or patent.	7.90

PAC Committee Members		
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PAC Member 3 Name: Upinder Kaur	UID: 27954	Recommended (Y/N): Yes

Final Topic Approved by PAC: **Automated Diagnosis of Brain tumor in MRI images using Deep Learning techniques**

Overall Remarks: Approved

PAC CHAIRPERSON Name: 13714::Dr. Prateek Agrawal **Approval Date:** 11 Apr 2024

Abstract: -

Brain is one of the most vital organ in human nervous system. Brain contains most lacks of nerves connected and communicating each other. An unusual growth or increase of nerves in the brain, which may affect the actual working of the brain, is called a Brain tumor. In the modern day the brain tumor was detected by traditional way of laborious and traditional approach. However, this lab analysis was too time consuming, which may lead to the increase the severity of the tumor cells. To address this issue, automated brain tumor detection techniques was introduced, which will help the early detection of tumor cells and helps for the timely medicating. In this study, The Cancer Imaging Archive was utilized as a dataset. The pre-processing and data augmentation techniques have been applied for training purposes using various deep learning models. The optimizers were used to determine stronger dataset to train the model. The pre-processed dataset were passed to the model to train on it. The deep learning model Convolutional Neural Network is used with the various pre-trained models like ResNet50, Xception, VGG19, MobileNetV2, InceptionV3. The accuracy of the different models was validated and tested to obtain the model which gives the good accuracy. This research primarily focusing to help the medical professionals in their efforts to detect brain tumor through the use of imaging techniques.

Declaration: -

I hereby declare that the research work reported in the dissertation/dissertation proposal entitled "AUTOMATED DIAGNOSIS OF BRAIN TUMOR IN MRI IMAGES USING DEEP LEARNING TECHNIQUES" in partial fulfilment of the requirement for the award of Degree for Master of Technology in Computer Science and Engineering at Lovely Professional University, Phagwara, Punjab is an authentic work carried out under the supervision of my research supervisor Jaspreet Kaur. I have not submitted this work elsewhere for any degree or diploma.

I understand that the work presented herewith is in direct compliance with Lovely Professional University's Policy on plagiarism, intellectual property rights, and the highest standards of moral and ethical conduct. Therefore, to the best of my knowledge, the content of this dissertation represents authentic and honest research effort conducted, in its entirety, by me. I am fully responsible for the contents of my dissertation work.

SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in MASTER OF TECHNOLOGY dissertation proposal entitled " AUTOMATED DIAGNOSIS OF BRAIN TUMOR IN MRI IMAGES USING DEEP LEARNING TECHNIQUES ", submitted by Sri hari gupta K at Lovely Professional University, Phagwara, India is a bonafide record of his original work carried out under my supervision. This work has not been submitted elsewhere for any other degree.

Signature of supervisor

Jaspreet Kaur

Assistant Professor

Date

Counted signed by

Concerned HOD: ________________

HOD's Signature: ________________

HOD's Name: ________________

Date: ________________

Acknowledment

I would like to convey my most hearfelt and sincere gratitude to my guide Jaspreet Kaur of Lovely Professional University, for her valuable guidance and advice. Her willingness to motivate me contributed tremendously to achieve the goal successfully.

Table of Contents

Keywords

Pre-processing, CNN, ResNet50, Xception, VGG19, MobileNetV2, InceptionsV3.

Chapter 1

Introduction

Human brain controls every aspect of human actions ranging from physical activities, thoughts to emotions. Brain is functioning by sending and receiving the signals to all over the body via neurons. Brain and Spinal cord connected each other and forming central nervous system (CNS). Brain tumor is the growth of the abnormal cells in the brain. The brains anatomy is very complex, each and every part of the brain is responsible of different functions. Brain tumor can develop in any part of the brain, including the protective lining and the skull base, the brainstem, the sinuses and the nasal cavities. In this recent years, brain tumors are the deadliest disease with highest death rate.

Detecting the brain tumor is big task, scanning the brain to locate the tumor cells. There are many different scans such as Magnetic Resonance Images (MRI), Computed Tomography(CT), Biopsy, Angiography. In this project Magnetic Resonance Image (MRI) dataset were used. MRI images are sequenced as T1 weighted (T1W), T2 weighted (T2W), Fluid attenuated, Fluid Attenuated Inversion Recovery (FLAIR), Proton Density. In this project the FLAIR MRI image dataset is used to train the model. Advantages of using FLAIR MRI images is, it selectively suppresses the fluid signals such as cerebrospinal fluid (CSF), it will differentiate different leisure and tissue. However, the detection in traditional method takes very long time and it will increase the severity in that time.

With the help of the modern computer and latest technology brain tumor can be detected at early stage and correct medications will be provided at the right time. The FLAIR MRI images were pre-processed to ensure that the creating model should receive correct format to train without any interruption. The shape of the dataset should be in same size for avoiding the errors. Normalizing the data, removing the noise in the data is done in pre-processing state.

Data augmentation is a technique which is used to create modified datasets by using the given dataset. With this technique we can ensure that we can create a dataset without losing the features. Data augmentation is a technique which will rotate, shear, scale, flip the dataset and saving it as the new inputs. This technique will be effective when there is shorter in dataset. The augmented data were visualized and see how well the dataset was spread over the target, information of the datasets.

The Convolutional Neural Network (CNN) takes augmented images as input and train the model. The pretrained model were included and the dataset passed to it. Resnet50, Imagenetv3, Xception, VGG19, MobileNetv2 pretrained models were included. The last layer of this models were cut down and the output of is passed to the network for the classification. The output is tested with the metrics such as Precision, Recall, Specificity, F1 Score, Accuracy, Confusion matrix. The calculated metrics shows that the models performance over the dataset.

1.1. Pre-processing : -

This technique refers to the data integrity, cleaning, transforming, reduction, normalizing, discretization the data. The resizing technique is used to resize or converted the image into the same size. To ensure the images are in the same size so that the model will train correctly. Image transformation leads to rotating, scaling, shearing, flipping the images to create a dataset with different information without losing the originality. Discretization involves separating the continuous values to the discrete values. Normalization is a technique where the intensity levels where scaled to common range of 0 to 1, so that it is easy to visualize and train the model. Pre-processing is the cleaning the data that means that to remove the noise in the image. There are many pre known noises like Gaussian noise, Rayleigh noise, Exponential noise, Uniform noise, Salt and pepper noise, periodic noise etc. With these help of pre known noises the noise in the image was removed and it produce the approximately noise free image. Feature selection is the important process that the selecting a relevant feature or subset of the requirement from the image, so that the training can be done easily. Sampling the subset from the dataset helps to reduce the size of the dataset with preserving the important information. Here in the pre-processing of the dataset was done by the normalization of the data, sampling the data. It helped the model to overcome the data redundancy.

1.2. Segmentation

The MRI image segmentation is very difficult because the many MRI images will be produced at the time of scanning and it made the task tougher to the physician to divide the images. At the time of taking MRI images, the images will be overlapped and it was confusing to view. So the task is to separate or partition the MRI images without any overlapping and in good condition. Segmentation is a task to partition the digital pictures into discrete group of pixels. In the The Cancer Imaging Archive (TCIA) dataset the images T1 weighted, T2 weighted, Fluid Attenuated Inversion Recovery (FLAIR) images were grouped for 110 patients and stored is folder format. Here we are using Fluid Attenuated Inversion Recovery (FLAIR) images to train the model. The FLAIR images were separated from the group and the mask image of the image was separated. Mask image is a image which only contains the tumor cells. This separation will help the model to train correctly and majorly helps to test the model by visualizing the tumor cells that were predicted and in the mask cell. The FLAIR image and the Mask images were given below.

1.3. Feature extraction: -

Feature extraction of the image refers to the process that transforms the raw input data into numerical features processed with the preserving the original dataset. The raw data is converted into the numerical features because the model can’t train on the raw data it yields poor results, since the raw data contains lot of information redundancy in it. The Convolutional Layers in the model is responsible for the feature extraction from the image. Convolution layer contains the filters which is also known as the kernels which detect the features like edges, colours throughout the image. If the image is passed to the convolution layer the size of the image will be decreased as well as it will bring the all information in the field together in the single pixel. The group of convolution layer is formed in Sequential manner so that the features of the image was extracted and converted into the smaller size. There are many convolutional layer for eg. 2D convolution, 3D convolution. The 2D Convolution (conv2D) deals the 2 dimensional image where the filters in the convolution slide all over the image, performing an elementwise mathematical operation. There are many mathematical operations can be performed like multiplication, average, nearest neighbour etc. As a result, after this operation, it will have compiled the results in the single pixel based on the pixel location. Same operation will be repeated all over the image, so as the 2D image or 2D matrix of certain features will be transformed into the different 2D images or 2D matrix of features.

Chapter 2

Problem Statement: -

In today's fast-paced world, as technology advances decisively, so does illness. The rate of advancement or the discovery of illnesses, diseases, and psychological problems goes up proportionately. Greater countries like India had a significantly greater chances viruses and infectious disease risk. With the aid of modern technologies, the government is introducing more safety measures to combat this.

Brain tumours are among these serious illnesses. A brain tumour is a condition that kills numerous individuals. Recent statistics technological demonstrate that approximately 40,000 and 50,000 people get diagnosed with brain tumours annually. The percentage of people who die from these cancers for malignant brain tumours is 65.6%. The Indian government continues to track public health and precisely identifying ailments. High-tech devices and technologies were widely available in modern hospitals, enabling early detection and early medication administration. This research is contributing to the discovery of the most effective method for early brain tumour detection.

Numerous medical centres employ different methods to recognise brain tumours. Here, we're contrasting those methods with other models that we developed. And choosing which architecture yields the greatest results in terms of accuracy and dependability. The present study aims to identify and categorise brain tumours using many pretrained models, ultimately providing the most accurate and dependable model.

For detecting and identifying the brain tumor detection and classification, The Cancer Imaging Archive (TCIA). This dataset contains the Magnetic Resonance Images (MRI) images of 110 patients. This MRI images is collected together with the Fluid Attenuated Inversion Recovery (FLAIR) abnormality task.

The CNN is implemented with the convolutional layers, Max pooling layers, flatten layer, and fully connected layer. The task here is to utilize the potential of the CNN model to determine the classification and segmentation of the tumor with minimizing the misclassification.

Then the task is to fine tune and train the dataset with the pre-trained models. The first task is that the cutting down the last layer of pre-trained model and adding it to the fine-tuned layer. To determine the accuracy of those various pre-trained models and to determine and state the finding of which of the following model giving more accuracy of detecting and segmenting the tumor.

Chapter 3

Objective of Study

The main goal of my thesis is on the early identification of tumours by carrying out the use of MRI scans of the human brain. The primary objectives of this research are as follows:

1. The main objective of the study is to identify and classify the brain MRI images with the benign and malignant tumor cells. After classifying the dataset the model the identified tumor cells is visualized separately. So that it is easy to understand and classify it.

2. Result comparisons across different CNN architectures. The result of the various deep learning models like CNN, and the pre-trained models like the ResNet50, Xception, InceptionV3, VGG19, MobileNetV2 is determined and calculated, then it is stored in the result variable. The results of the various models were then compared each other to state the highest accuracy provider.

3. Establishing the normalized form of the brain MRI image storage or database by training these various deep learning models. The weights of the models where stored separately after the training of every epoch. Those weights were used to evaluate the model on how it was trained with the testing datasets. Those weights are then used to segment tumor cells and determining the mask image.

Chapter 4

Literature Survey

Brain tumor detection in MRI image is quite a bigger challenge in medical field. Most of the related work in the field of Brain tumor involves the data pre-processing, feature extraction, detection of tumor. The existing models were built in Deep learning and Convolutional Neural Network (CNN).

Ramtekkar et al. (2023) proposes a system for brain tumor detection model. The authors used Kaggle dataset for brain tumor classification. The model involves pre-processing, filteration, segmentation, feature extraction, optimization, convolutional neural network (CNN). In pre-processing, noise in the MRI images were removed by converting the images into grayscale, and filter it out by filtering methods. The MRI images are segmented into non-overlapping-sections. To identify the boundaries threshold and histogram-based segmentation process is used. Feature extraction is done by contrast, correlation, homogeneity, entropy, energy is used. Optimization techniques like Particle swarm optimization (PSO), Genetic Algorithm (GA), Gray wolf optimization (GWO) is used to select the fittest image feature. Then, the images are passed to the CNN model where the model identifies the tumor in the image and classify accordingly. Finally, the model obtained the accuracy of 98.9%.

Kumar et al. (2023) suggests a different method of brain tumor classification. The authors used cancer imaging archives datasets (ACRIN-DSC-MR-Brain (ACRIN 6677/RTOG 0625), CPTAC-GBM, and ACRIN-FMISO-Brain (ACRIN 6684)). The model is comprised of pre-processing, segmentation, feature extraction and classification. In pre-processing the images were resized to organize it in same shape as 64 X 64. Then the grayscale and thresholding were applied to increase the intensity of tumor region. In segmentation, instead of using tradition approach the authors used dual-tree wavelet transformation (DTWT) and used low pass filter. For classification, performed classification using pre-trained model and transfer learning. The Soft-max classifier is used for classification and probabilistic function in transfer learning. UNet, AlexNet,VGG16, ResNet50 models were used. The ResNet 50 model is able to classify the malignant and benign class with 98.4% and 99.3% .

Nassar et al. (2024) proposed a method for brain tumor classification technique in hybrid deep learning techniques. T1W-CE MRI dataset were used which includes meningioma, glioma, and pituitary MR image. Data augmentation technique were used only to training techniques and for testing the original dataset is used without any pre-processing for the originality. The image was resized to fit the CNN model's input image size. Here five altered fine-tuned pretrained models were used such as GoogleNet, AlexNet, ShuffleNet, SqueezeNet, and NASNET-Mobile to distinguish their performance in classifying different categories of brain trumors. The model evaluated using standard performance measures such as overall accuracy, specificity, sensitivity, f1-score, and confusion matrix. The NASNet model yielded the accuracy of 97.50%.

Razzaq et al. (2024) the authors proposed optimized linear support vector network (oLSVN) based brain tumor detection using MRI images. The data set used is comprised of 5710 images divided into testing and training datasets. The proposed methodology consists of pre-processing, feature extraction, hand crafted features, high quality feature selection, hybrid feature (HF) selection, Bag of Feature(Bof). The metrics like Precision, Recall, Specificity, Sensitivity, F1-score, Mathews Correlation Coefficient (MCC) is calculated to measure the model performance. The proposed model produces the accuracy of 87.4% with an execution time of 243.6 sec.

Haq et al. (2023) suggest MRI based deep learning approach for efficient classification of brain tumor. The researchers utilized the Multimodal Brain Tumor Image Segmentation Benchmark (BraTS) brain tumor 2018 dataset as an input. The proposed model consists of pre-processing, data augmentation, segmentation process, Deep convolutional neural network (DCNN). Denoising techniques were used to eliminate Gaussian noise, Salt and Pepper noise, and Speckle noise from the MRI images. Wiener filter and median filter are used to minimize the root mean square errors. A hybrid method focussed on fuzzy and brainstorm optimization technique was used for segmentation. A deep convolutional neural network is designed and intensity normalization is tuned for each tumor type. Leaky ReLU (LReLU), Soft-max were used as a activation functions. The model runs successfully with the accuracy of 96.5% in BraTS 2018 dataset.

P.Ramya et al. (2021), authors implemented segmentation of brain tumor using cluster ensemble and deep super learner classification of MRI. The model they created consists of Image registration, pre-processing, clustering methods like K-means clustering, Gaussian Mixture Model (GMM), Fuzzy based Clustering, Self-organizing map (SOM) and Cluster ensemble. Firstly, the raw dataset T1, T2, and FLAIR MRI of test images is pre-processed using Laplacian Cellular Automata Filtering (LCAF). The registered image is first segmented using K-means, fuzzy and SOM. The clustered matrix of each algorithm of each algorithm is grouped for ensemble to form final segmented image. Deep Super Learning (DSL) method added advantages to improve the classification. The proposed work producing good results with the accuracy of 96.3% and 95.8%.

Chanu and Thongam (2021), the authors stated the deep learning methods to detect the brain tumor from the MRI images. The proposed techniques are 2D-CNN, Image acquisition, Image pre-processing, cropping, Image rotation, Noise filtering, Image scaling, and Image augmentation. Here the unpre-processed images were processed to single format of image as PNG. Noise filtering is defined to be a random dissimilarities of image intensity which is the grains in the image. The Convolutional Neural network was built with the convolutional layers, non-linear units like Rectified linear unit (ReLU), Max min average pooling were used, flattening layer, fully connected layers are used. The model acquires the accuracy of 97%.

Kalyani et al. (2023) proposes the deep learning techniques for analysis of brain tumor on MRI brain tumor images. The techniques used in this model is Faster R-CNN, YOLOV3, YOLO-tiny, object detection. The dataset which is used for this model is Microsoft common objects in context (MSCOCO) datasets. YOLOV3 in this model uses Darknet-53 architecture which have many convolutional layers. Normalization of the dataset is applied through batch normalization. YOLOV3 – tiny is an another variant of YOLOV3 with a reduced depth of CNN. Moreover, YOLOv3 detector units has been behave like recognition unit. The proposed model gives the accuracy of 93.14%.

Rammurthy D et al. (2020) describes a brain tumor detection by using the optimized technique Whale Harris Hawks Optimization (WHHO). In the proposed system the segmentation is performed using cellular automata and rough set theory. The image features are extracted from the segments includes tumor size, Local optical oriented pattern (LOOP), mean, variance and the kurtosis. Deep Convolutional neural network (DCNN) is used to train the model with the WHHO which has been implemented with whale optimization technique. The model producing the accuracy of 81.6%.

Asif et al. (2023) has produced an enhanced deep learning method for multi-class brain tumor classification using deep transfer learning. The architecture used in the paper are Xception, DenseNet201, DenseNet121, ResNet152V2, and InceptionResNetV2. The Figureshare benchmark dataset is used to assess the performance of the proposed model. The MRI data were pre-processed and cropped to ensure the maximum accuracy. Also, the hyperparameter and optimization procedures are implemented for attaining better and robust model. The model with the Xception produces the higher accuracy of 99.67%.

Amin et al. (2018) has stated that different approach for detecting the tumor by the feature fusion and machine learning. Here the author used the benchmarked dataset of BRATS datasets in different years (2012 – 2015). For calculating the metrics of the model precision, recall, accuracy, specificity is used. To segment the tumor cells in the MRI image is done by pixel based experimental results. Gabor wavelet transform and the histogram is employed to extract the features. Classification of Brain MRI images into benign and malignant is done by using the model Random Forest classifier. By employing this model with the added segmentation and feature extraction it reached the accuracy of 98%.

Anil et al. (2019) used a transfer learning approach to detect the tumor cells in brain. The author used VGG16, VGG19, Alexnet deep learning model to train on the brain MRI datasets. In pre-trained models only the top layers were included and the output of the top layers is transferred to the fine tune layers. Among these pre-trained model, the VGG19 model gave the highest accuracy of 95.78%.

Sajid et al. (2019) has produced the innovative approach for detecting the brain tumor by using the deep learning models with MRI datasets. The author used BRATS 2013 brain tumor datasets for the training of the model. The proposed model deals with the major problem overfitting by means of reducing it. For that the datasets were pre-processed, batch normalization, regularization is done before passing to the model for training. The dataset is trained under the deep learning models feed forward network, CNN and post processing steps. By utilizing this architecture, the model achieves the accuracy of 91%.

Yamashita et al. (2018) introduces a different approach of application in radiology through the CNN. The author stated two challenges in applying the CNN to radiology dataset is small dataset and the overfitting. Here stated that to reduce the overfitting is by increasing the number of dataset so that the model will generalize the dataset. The second solution as regularization of weight decay and dropout. For training a small dataset the pre-trained models or transfer learning approach like AlexNet, VGG, ResNet, Inception model can be employed.

Kokila et al. (2021) has shown an approach to identification and classification of brain tumor by using the deep learning techniques. To train the deep learning models Kaggle dataset repository of cancer Imaging is used. The CNN based classification is done by multi-task classification. The identification of brain tumor location is done by using CNN model segmentation. This proposed model achieved accuracy of 89%.

Chapter 5

Proposed research methodology

The proposed methodology contains following steps:

Step 1: For automated diagnosis of brain tumor The Cancer Imaging Archive (TCIA). This dataset contains the Magnetic Resonance Images (MRI) images of 110 patients. This MRI images is collected together with the Fluid Attenuated Inversion Recovery (FLAIR) abnormality task. The image used here is in the format of Tag Image File Format (TIFF) with 3 channels per image. The dataset collected is here named as the case id of the patient id and case id.

Step 2: The TCIA image dataset is then passed to the pre-processing of the datasets. There is many pre-processing techniques like integrity, cleaning, transforming, reduction, normalizing, discretization the data. The resizing technique is used to resize or converted the image into the same size. To ensure the images are in the same size so that the model will train correctly. Normalization is a technique where the intensity levels where scaled to common range of 0 to 1, so that it is easy to visualize and train the model. Here in this study the pre-processing of the dataset was done by the normalization of the data, sampling the data. It helped the model to overcome the data redundancy.

Step 3: The next step is to segmentation of the dataset without overlapping and in good condition. Segmentation is a task to partition the digital pictures into discrete group of pixels. In The Cancer Imaging Archive (TCIA) dataset the images T1 weighted, T2 weighted, Fluid Attenuated Inversion Recovery (FLAIR) images were grouped for 110 patients and stored is folder format. Here we are using Fluid Attenuated Inversion Recovery (FLAIR) images to train the model.

Step 4: The dataset contains dataset for 110 patients with over 3500 images in it. These dataset is to be separated to train the model. The separation is made as three divisions namely training dataset, Validation dataset and the training dataset. The training and validation dataset is used to when the model is in the training phase.

Step 5: The Convolutional Neural Network (CNN) model will train on the training dataset. To check whether the model is training well by using the validation dataset. If the validation accuracy is not increased over certain epochs, then the early stopping method will stop the training of the model. Once the model is trained with the training and the validation dataset, to determine the performance of the model, it is tested with the testing dataset.

Step 6: After the training of the CNN model, it is tested with the metrics like confusion matrix, precision, recall, accuracy, specificity, classification report. Once the training of the CNN model the dataset were tested with the various pre-trained models like ResNet50, Xception, InceptionV3, MobilNetV2, VGG19.

Step 7: The pre-trained models were utilized with cutting down the last layer which the classification of ImageNet dataset of 1000 classes. The model used here have two class classification. The top layer of the pre-trained model is then connected with the fine tuning layer to classify the images as the normal and tumor contains images. The pre-trained models were trained on the training dataset with the inclusion of validation in every epochs. The weights were then saved separately for the segmentation of the dataset.

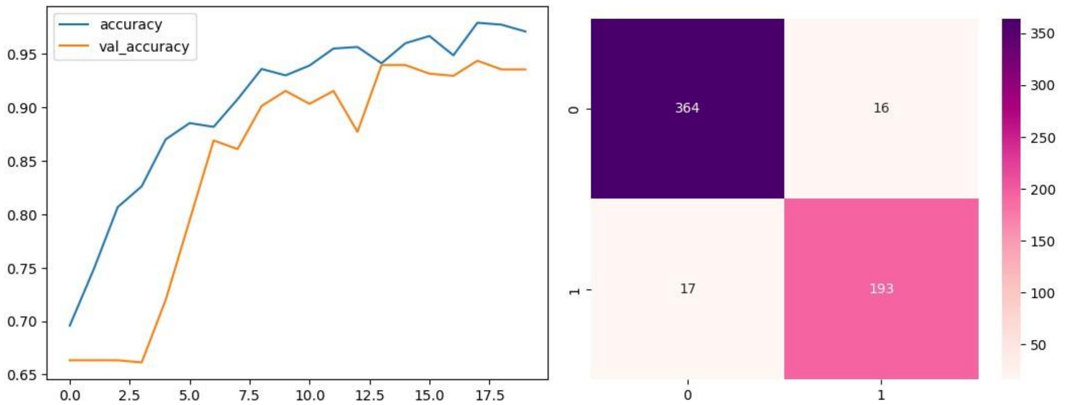
Step 8: With the saved weights the model is then used for the segmentation of tumor cells from the input MRI images. The segmented images are visualized for the testing on how the model trained. Then the segmented image is then compared with the mask images in the TCIA image dataset. From the comparison we can come to know about the accuracy of segmenting and predicting the tumor.

Step 9: After training of all the pre-trained models, it is tested with the metrics like confusion matrix, precision, recall, accuracy, specificity, classification report. Out of this models the InceptionV3 model provided the highest accuracy of 95%.

CHAPTER 6

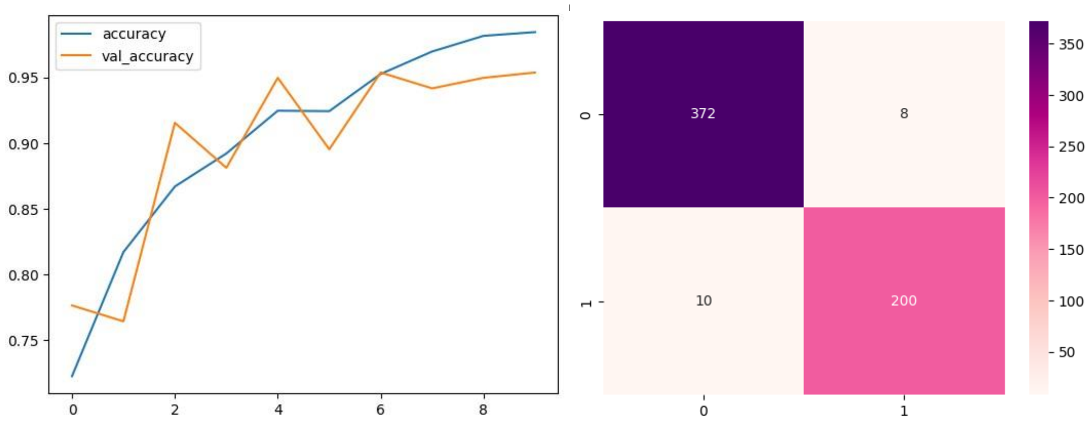
Experimental Results

The dataset for the brain tumor is pre-processed, segmented, extracted, augmented and the deep learning models were introduced for the dataset. The deep learning models were included into this architecture and run successfully. The pre-trained models like ResNet50, Xception, Inceptionv3, VGG19, MobileNetV2 were produced with the good accuracy of 94.4%, 96.9%, 94.23%, 64.4%, 62.03%. The validation accuracy and the accuracy is analysed and plotted in a graph. The confusion matrix is calculated with the precision, recall, F1 score. From the below shown graph and in the scatter matrix it is quite evident that the model performs and trained well in the model.



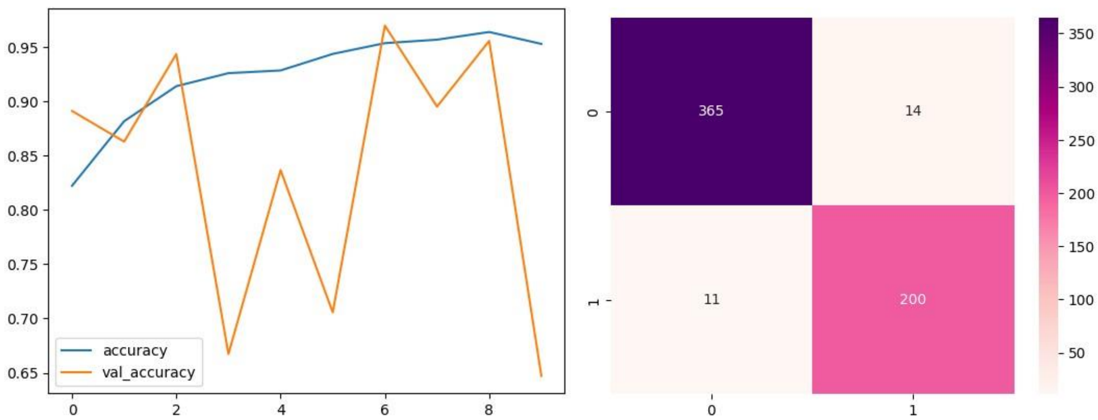
	precision	recall	f1-score	support
0	0.96	0.96	0.96	380
1	0.92	0.92	0.92	210
accuracy			0.94	590
macro avg	0.94	0.94	0.94	590
weighted avg	0.94	0.94	0.94	590

Figure 1. ResNet50 model accuracy chart, confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.97	0.98	0.98	380
1	0.96	0.95	0.96	210
accuracy			0.97	590
macro avg	0.97	0.97	0.97	590
weighted avg	0.97	0.97	0.97	590

Figure 2. Xception model accuracy chart, confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.94	0.97	0.96	380
1	0.94	0.89	0.92	210
accuracy			0.94	590
macro avg	0.94	0.93	0.94	590
weighted avg	0.94	0.94	0.94	590

Figure 3. InceptionV3 model accuracy chart, confusion matrix and classification report.

S.no	Models	Accuracy
1	ResNet50	94.4067
2	Xception	96.9491
3	InceptionV3	94.2372
4	VGG19	64.4067
5	MobileNetV2	62.0338

Table 1. Result of the pre-trained model.

Chapter 7

Conclusion

The design and development of the deep learning model for the dataset's classification of brain tumors is the study's primary goal. The task of classifying brains into benign and malignant classes is difficult because of the substantial amount of complexity in the dataset. The suggested models have been designed to function with a comparatively high amount of picture data. The work provides demonstrations for segmentation, feature extraction, and pre-processing of data. The visualization and augmentation of the dataset are demonstrated. The dataset was explored using the pre-trained models, and the model accurately predicted the location of the tumor. For the purpose of to detect brain tumors, five robust deep learning pre-trained models were used. Good accuracy was obtained from the pretrained models ResNet50, Xception, Inceptionv3, VGG19, and MobileNetV2. With a 95.7% accuracy rate, the InceptionV2 model yielded excellent outcomes for the TCGA dataset. The study indicated the model with the best accuracy provider among the ones listed above. Compared to other models, this one is better and has a higher classification accuracy. The plan is to build on this work in the future to further improve the models' accuracy in performance.

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Appendix

Artificial Neural Network

Artificial neural network is the combination of community of neurons, which is made inspired by the working of the human brain. Each neuron in the network is well connected, it means one artificial neuron is connected with the input from the output of other. Every neuron in the network is responsible for performing some mathematical operations on the input they taken and those neurons provides one output which is the input for the next neuron. Each neuron is connected with the activation function which is used to introduce non-linearity in the data. Those activation function will decide whether to activate the output or not.

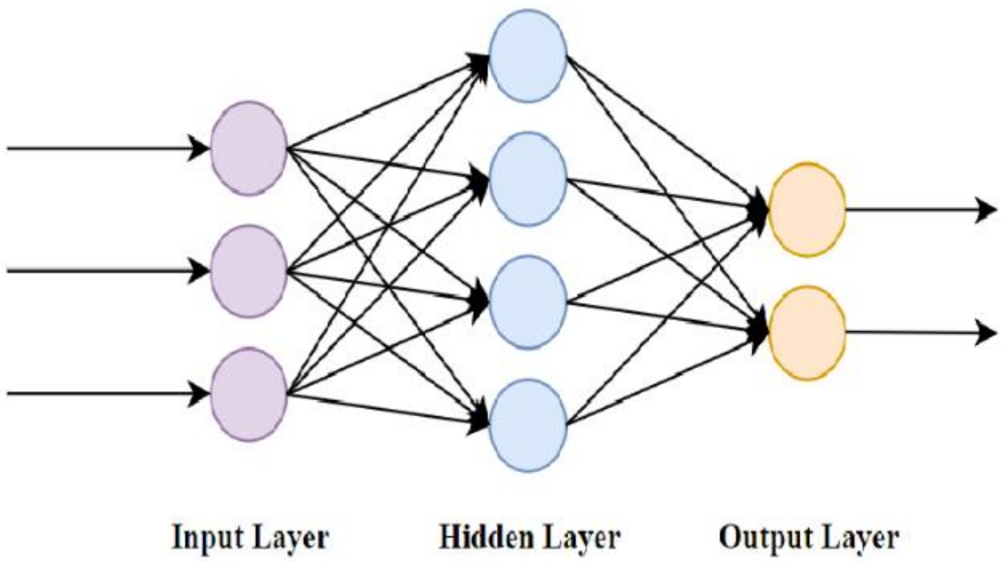

Figure 4. The basic architecture of Feed forward network.

Convolutional Neural Network

Convolutional layer in the CNN is important part as it is responsible for the extraction of the main features from the image of multiple layer in sequential manner. A general term for convolution is the grouping in mathematics. The main work of the convolution is to combine two matrices with the mathematical equations to create a third matrices. The Convolutional layer hover over the entire images by moving the Strides and Filters. Filter is responsible for the extraction of the features from the images. The filter will hover over the image by the Stride value. Stride will say that how much pixel does the filter need to be moved further. For example, if the image of **4X4** and the filter size of **2X2** and stride of 1 is applied, then the filter starts from the 1st pixel and it moves to the 2nd pixel and follows till the last pixel of the image. In some cases, applying of filters and strides may results in losing some features in the images. Means, the information in the corners of the image is not extracted. To overcome this problem, the Padding comes into the model. It will add the frame of 0's to the image. So that every nook and corner information of the image is extracted. Every convolutional layer is connected with the activation function. Activation function in added in the convolutional layer is to ensure the non-linearity in the model and to handle and learn more complex relationship in the data. There are many types of Convolutional layer according to the dimension of the data such as conv1D, conv2D, conv3D. In the proposed model of Convolutional neural network there are there are three convolutional layers (conv2D) added in the sequential manner. First convolutional layer with depth of 128. The input is passed in this layer of convolutional layer with the size of **(256,256,3)** which is 3 channel image. The extracted features are passed on to the following sequence of convolutional layer with the depth of 64 and 32. Rectified Linear unit (ReLU) activation function is added in all layers of the convolutions.

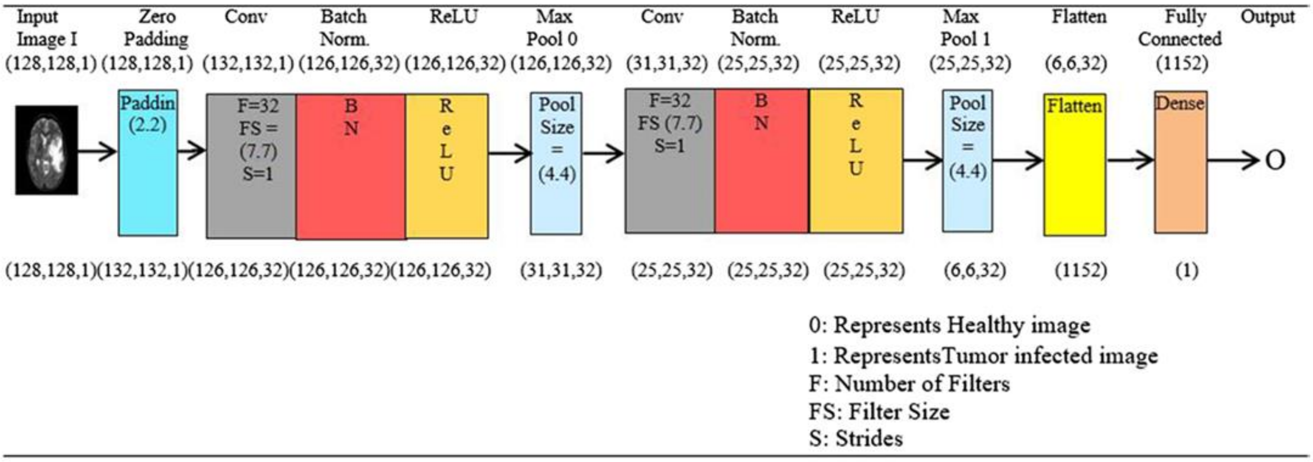

Figure 5: Workflow of CNN. **Ramtekkar et al. (2023)** [1]

Pooling layers in the CNN is responsible for filtering out and reduce the dimension of the extracted features with some mathematical operations from the image. The Pooling layer is responsible for reducing the dimension of the input feature maps. Pooling in general it means that the act of combining two or more things. As the name says it will do some mathematical operations in the input like finding maximum, minimum, average, neighbour and reduce the complexity of the image to the model following. Pooling layers will down samples the volume of neural network by reducing the small translations in the features. There are two types of pooling layers widely used is MaxPooling and AveragePooling. Max pooling is the taking the maximum valued pixel in a particular patch of the feature maps. Average pooling is taking the average among the pixel in a particular patch of the feature map. In the proposed model, Maxpooling2D is used with the size of **2X2**.

Flatten layer act as the bridge between the convolution layer and the dense layer. The responsibility of the flatten layer is to change the shape of the feature maps. The output of the convolutional layer is in the form of multidimensional and the dense layer will accept the one dimensional input. So it makes the multidimensional layered features to one-dimension feature map.

In the architecture of the Convolutional Neural Network (CNN), the last layer is Dense layer or Feed Forward Network. Dense layer is used to classify the images based on the information extracted in the previous layers in the architecture. Dense layer is the combination of multiple neuron connected each other and getting input from the previous layer and perform mathematical operations on the given input before passing it to the next layer or the output layer. Every neuron in the dense layer is added with the activation function to ensure the non-linearity in the data. Rectified Linear unit (RELU) activation is used in the proposed system and the Soft-max activation function is used in the output dense layer because for the binary classification.

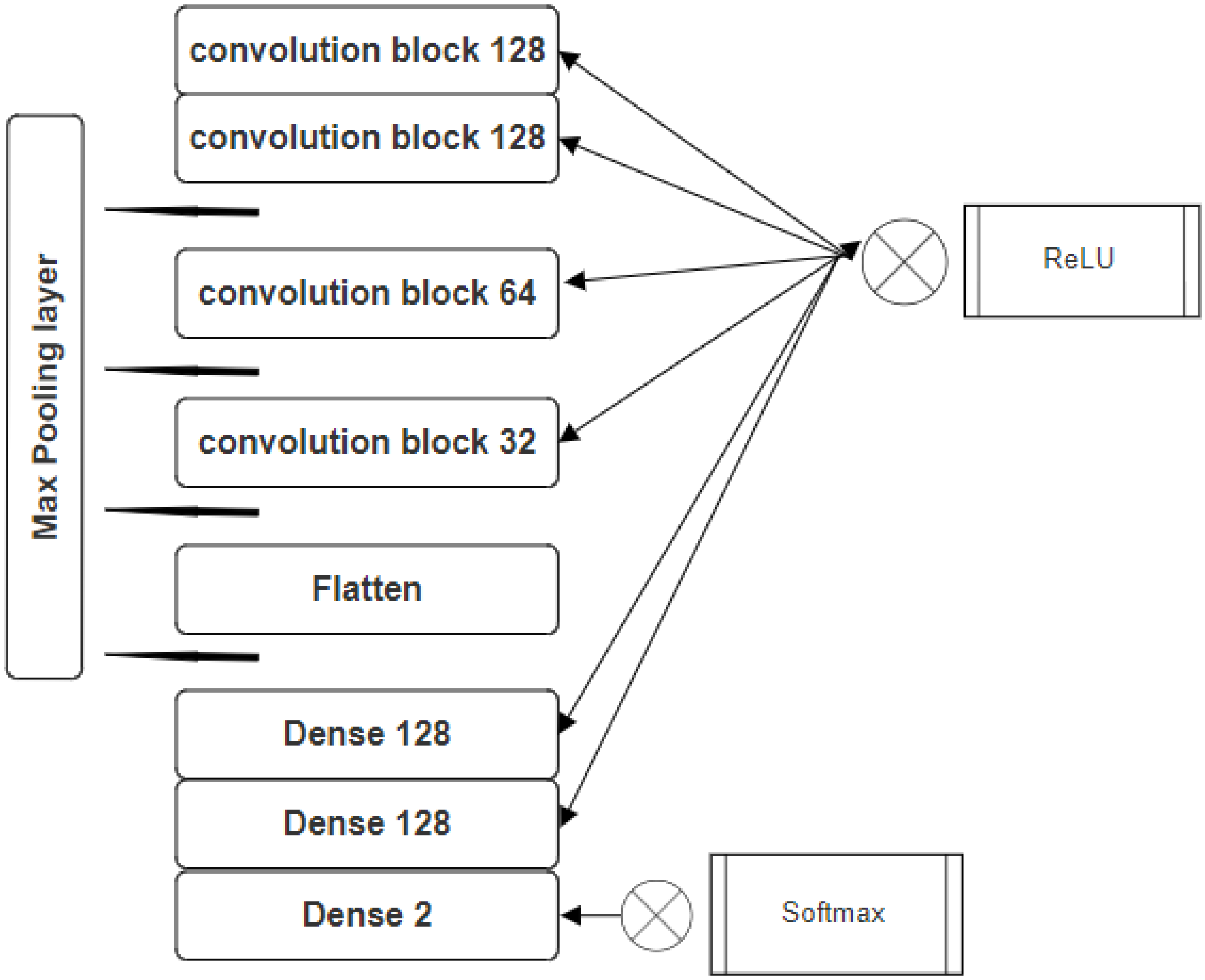

Figure 6. The above flowchart explains the architecture of CNN model.

ResNet50

Residual Network 50 (ResNet50) is the convolutional neural network which is formed with the residual blocks. Residual blocks are the block which is like Bottle-Neck architecture. This transfer learning approach of bottleneck is responsible for the highest predictive power and accuracy whenever making the prediction through the model. Bottleneck will convert the input images into compressed forms which is the lower dimension representation of the data.

ResNet50 is a powerful image classification model which will be used to train on large number of datasets and to achieve the state-of-art results. ResNet50 allows the models network to train and learn the residual functions that map the input to the desired output. The ResNet50 model will suffer with the problem Vanishing Gradient because the residual network models follow the novel way of building the convolutional neural network (CNN) using the concept called “Shortcut connections”. ResNet50 model is built on the basis of four steps such as the convolutional layers, the identity block, the convolutional block and the fully connected block.

InceptionV3

InceptionV3 is the successor of the GoogleNet model. InceptionV3 is the connection of multiple blocks of inception block. Inception blocks are a blocks which consists of different sizes of filter that allows the users to have a freedom to access the different features of filters, instead of restricting the user to stay in the single sized filters. InceptionV3 comprises of usual convolutional layers, pooling layers and fully connected layers. It also contains the main feature auxiliary classifiers.

Auxiliary classifier is used to predict the class labels and it helps to mitigate the vanishing gradient descent during the training by providing some signals to the following layers. This model will perform both the batch normalization and the regularization technique for normalizing and the generalizing the dataset.

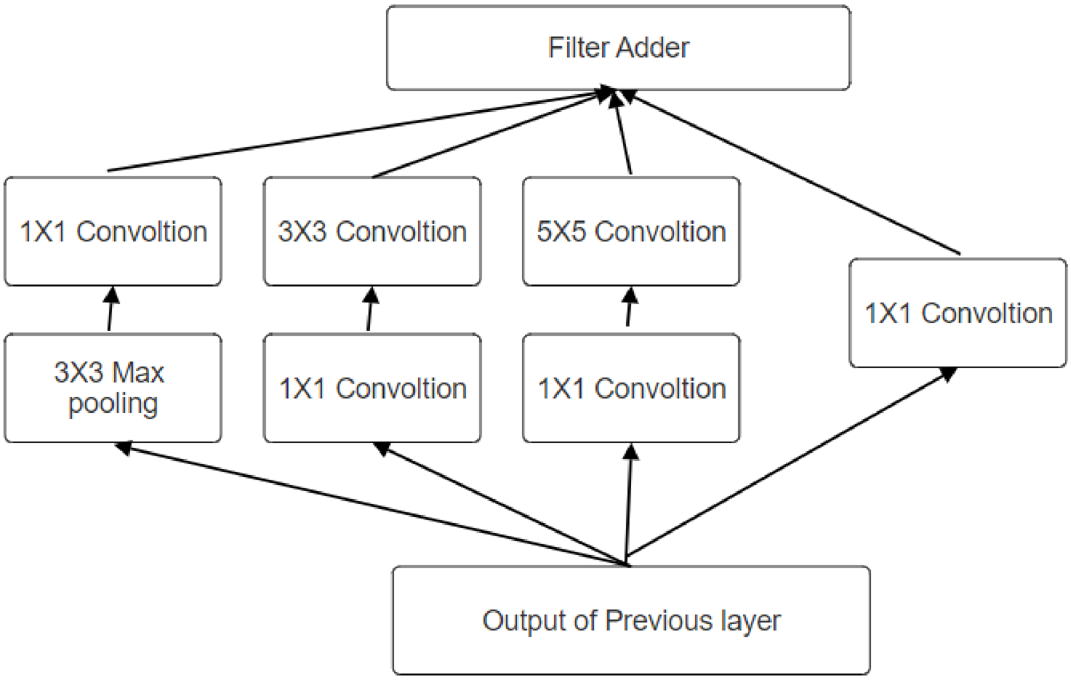

Figure 7. Architecture of Inception block.

Xception

Xception is a short form of “Extreme Inception” which is advance of the deep learning models. Xception brings revolution in deep learning by reducing the computational cost, computational time, input parameters. Regular models use the convolutional layers to extract the features. If the dataset has high spatial channels, then the computational cost, training time of the model will be increased proportionally. As this model will try to extract the information in all three channels parallel, the parameters count is increasing drastically. To overcome this problem Xception model is introduced. This Xception model will be trained with the depthwise convolution layers. This Depthwise convolution layers will work like if there is high spatial channel dataset is passed, then instead of doing all at once it will separately work on every channel and concatenate the channels with **1X1** convolution.

VGG19

The term VGG stands for visual geometry group, which is a group of convolutional neural network. Here the term 19 represents the layers of the CNN. In this architecture there was 16 layers of convolutional layers with 5 pooling layer and fully connected layers. Convolutional layers is connected is sequential manner. The ReLU activation function is used here to introduce the non-linearity in the data. The fully connected is responsible for the classification of the dataset with the extracted features.

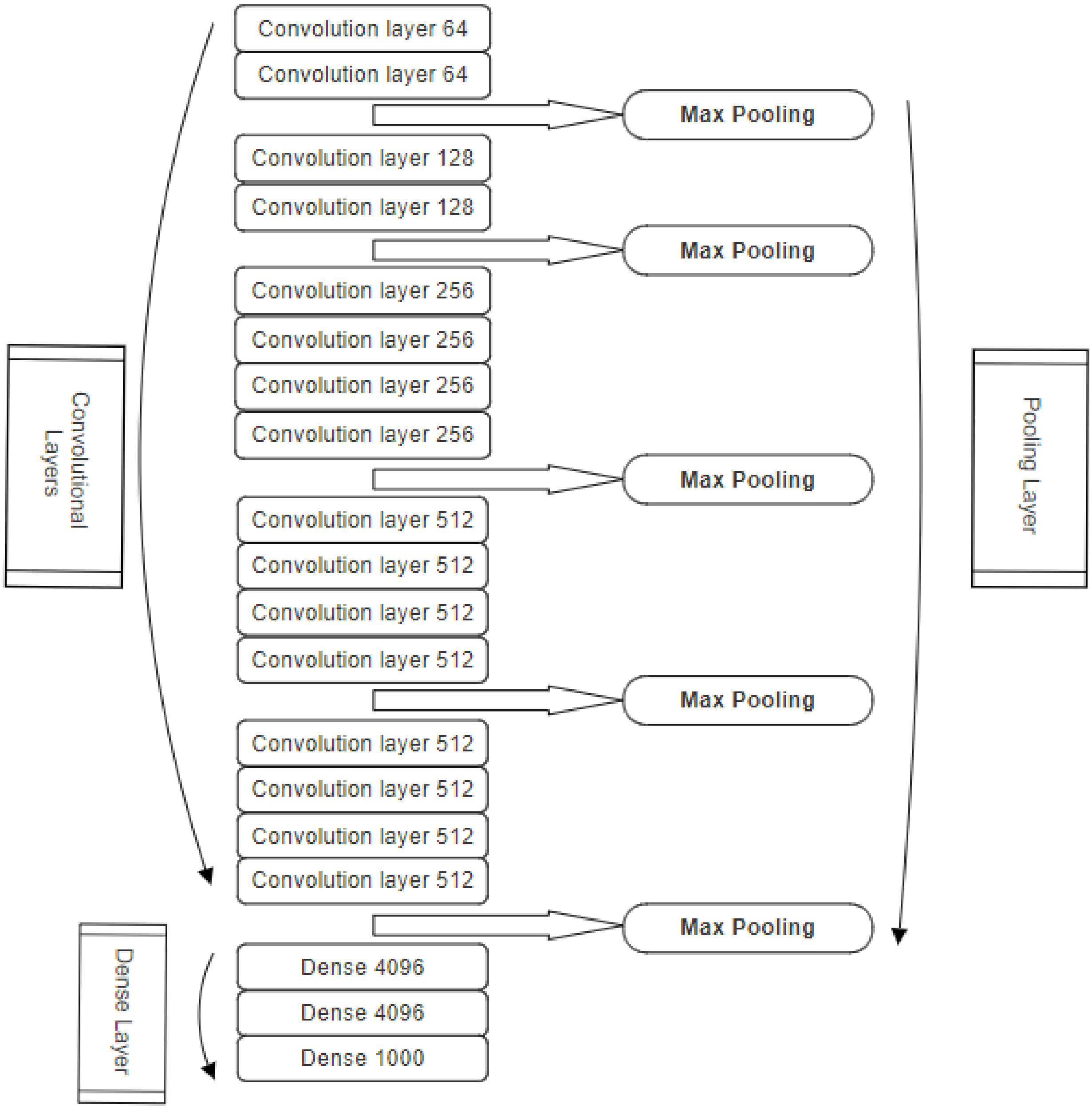

Figure 8. The above diagram represents the architecture of VGG19 model

MobileNetV2

The MobileNetV2 is an architecture of inverted residual algorithm. The inverted bottleneck approach reduces the memory requirement compared to classical residual blocks. This is achieved using depth-wise separable convolutions. Here it introduces two hyper-parameters width multipliers and the resolution multipliers. The width multiplier's job is to scale and modify the number of channels in every layer, always balancing performance and model size. On the other hand, the resolution multiplier's job is to lower the network's input resolution and even lower the computing demands while maintaining some degree of performance.

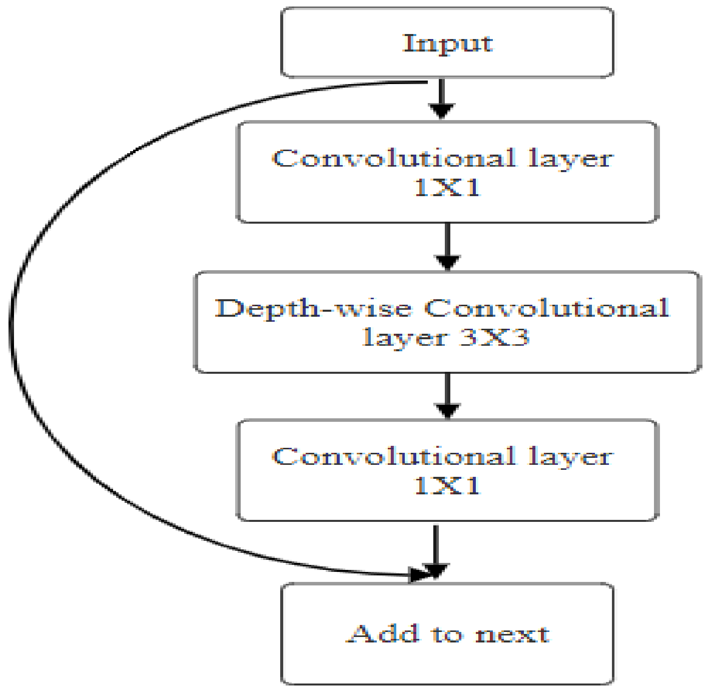

Figure 9. Inverse Residual block.